NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

EFFECTIVE TEAMING OF AIRBORNE AND GROUND ASSETS FOR SURVEILLANCE AND INTERDICTION

by

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June 2010

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704–0188

1. REPORT DATE *(DD–MM–YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From — To)*
17–6–2010	Master's Thesis	2008-06-20—2010-06-18

4. TITLE AND SUBTITLE

Effective Teaming of Airborne and Ground Assets for Surveillance and Interdiction

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Mark J. Muratore

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Naval Postgraduate School
Monterey, CA 93943

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Department of the Navy

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited

13. SUPPLEMENTARY NOTES

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. **IRB Protocol Number: N/A**

14. ABSTRACT

As Unmanned Aerial Vehicles (UAVs) become more prevalent on the battlefield, ground forces will have to increasingly rely on them for intelligence, surveillance, and reconnaissance (ISR), as well as target marking, and overwatch operations. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) simulation analysis tool uses Design of Experiments (DOX) to study of aspects of UAV surveillance characteristics in conjunction with ground-based interdiction teams. The goal is to reduce the time required to intercept and capture targets of interest. Through screening analysis, significant factors can be determined to build a model that will provide a ground commander with insights to aid in the tactical employment of his assets. We will examine different teaming strategies and coordination measures between searching and interdicting assets in order to study the effectiveness of the interdictor possessing an organic, tracker UAV. The objective of this research is to quantify the benefit or penalty of an additional UAV asset that is organic to a quick reaction force, in the context of the overall surveillance and interdiction operation.

15. SUBJECT TERMS

Unmanned Aerial Vehicle, Unmanned Aerial System, Linear Regression, Logistic Regression, Manned Unmanned Teaming, Teaming, Autonomous Systems, JMP

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*
Unclassified	Unclassified	Unclassified	UU	75	

Standard Form 298 (Rev. 8–98)
Prescribed by ANSI Std. Z39.18

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EFFECTIVE TEAMING OF AIRBORNE AND GROUND ASSETS FOR SURVEILLANCE AND INTERDICTION

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
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ABSTRACT

As Unmanned Aerial Vehicles (UAVs) become more prevalent on the battlefield, ground forces will have to increasingly rely on them for intelligence, surveillance, and reconnaissance (ISR), as well as target marking, and overwatch operations. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) simulation analysis tool uses Design of Experiments (DOX) to study of aspects of UAV surveillance characteristics in conjunction with ground-based interdiction teams. The goal is to reduce the time required to intercept and capture targets of interest. Through screening analysis, significant factors can be determined to build a model that will provide a ground commander with insights to aid in the tactical employment of his assets. We will examine different teaming strategies and coordination measures between searching and interdicting assets in order to study the effectiveness of the interdictor possessing an organic, tracker UAV. The objective of this research is to quantify the benefit or penalty of an additional UAV asset that is organic to a quick reaction force, in the context of the overall surveillance and interdiction operation.

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Contents

List of Figures

List of Tables

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Executive Summary

As Unmanned Aerial Vehicles (UAVs) become more prevalent on the battlefield, ground forces will have to increasingly rely on them for intelligence, surveillance, and reconnaissance (ISR), as well as target marking, and overwatch operations. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) simulation analysis tool uses Design of Experiments (DOX) to allow for the study of aspects of UAVs surveillance characteristics in conjunction with ground-based interdiction teams to aid in reducing the time required to intercept and capture targets of interest. Through screening analysis, significant factors can be determined to build a model that will provide a ground commander with insights to aid in the tactical employment of his assets. We will examine different teaming strategies and coordination measures between searching and interdicting assets in order to study the effectiveness of the interdictor possessing an organic, tracker UAV. The objective of this research is to quantify the benefit or penalty of an additional UAV asset that is organic to a quick reaction force, in the context of the overall surveillance and interdiction operation.

Utilizing design of experiments and statistical methods, we focused on identifying the significant factors that impact the Percentage of Targets Cleared and the Percentage of Time Surveyor UAV Performs Search for three different team types. These team types were (1) Surveyor, (2) Surveyor/Tracking, and (3) Surveyor with Tracker. We were able to determine, in all cases, that the factors with the greatest effect were the Search Area size and Team Type. Holding all other factors constant, we determined that as the Search Area increases, the Percentage of Targets Cleared decreases and the Percentage of Time Surveyor UAV Performs Search increases. We also discovered that possessing a tracking capability is clearly superior to no tracking capability. Of particular interest is that there was no significant difference between the Surveyor/Tracking and Surveyor with Tracker Team Types. Therefore, we conclude that possessing an augmented tracking capability does not increase the Percentage of Targets Cleared.

We also discovered that the Interdictor Transit Time was a significant factor for our model. The time required to reach targets of interest was the limiting factor in clearing those targets. We recommend studying various forms of mobility with differing speeds to determine which would increase the Percentage of Targets Cleared. Through field experimentation at Camp Roberts CA, we identified various real-world constraints that effect the response variables. Specifically, weather considerations and QRF proficiency in UAV operations will impact the responses. Nei-

ther of these considerations were modeled for our simulation and are worthy of future study.

The SASIO model can be used for any future studies involving teaming. It is recommended for future Naval studies in the use of Unmanned Underwater Vehicles (UUVs) and Marine Corps studies in the use of Cargo UAS as well as Unmanned Ground Vehicles (UGVs).

List of Acronyms and Abbreviations

AAW	Anti-Air Warfare
ACE	Aviation Combat Element
AO	Area of Operations
AOI	Area of Interest
C2	Command and Control
CASEVAC	Casualty Evacuation
CNO	Chief of Naval Operations
CONOPS	Concept Of Operations
DOX	Design of Experiments
EO/IR	Electro-Optical / Infra-Red
EW	Electronic Warfare
FOB	Forward Operating Base
FOS	Family of Systems
GCU	Ground Control Units
IED	Improvised Explosive Device
ISR	Intelligence, Surveillance, and Reconnaissance
MAGTF	Marine Air Ground Task Force
MAW	Marine Aircraft Wing
MCC	Mobile Command Center
MCTUAS	Marine Corps Tactical Unmanned Aerial System
MEB	Marine Expeditionary Brigade

MEF	Marine Expeditionary Force
MOE	Measures of Effectiveness
MUT	Manned-Unmanned Teaming
OAS	Offensive Air Support
RTB	Return to Base
SAR	Synthetic Aperture Radar
SASIO	Situational Awareness for Surveillance and Interdiction Operations
SSG	Strategic Studies Group
STUAS	Small Tactical Unmanned Aerial System
TOC	Tactical Operations Center
TTP	Tactics, Techniques, and Procedures
UAS	Unmanned Aerial Systems
UAV	Unmanned Aerial Vehicle
UCAS	Unmanned Combat Air System
USMC	United States Marine Corps
UUV	Unmanned Underwater Vehicle
VMU	Marine Unmanned Aerial Vehicle Squadron

Acknowledgements

First and foremost, I would like to thank Professor Timothy Chung for all his hard work and hours of patience as we struggled to build our model. His calm, reassuring tone and assurances that we were always in a "Happy Place" helped put me at ease during this arduous process. The hours of programming and statistical discussions were the best learning experiences I had at the Naval Postgraduate School. Second, I would like to thank Professor Rachel Johnson for her patience and countless hours of dedication to ensure the accuracy of the statistical analysis of my thesis. Thanks to my second reader, Major Chad Seagren, who came aboard late but proved to be an extremely valuable asset to my thesis team. Thanks to all of you. Finally, I want to thank my family. Thanks to Grace and Nicholas for always bringing joy to my day and a smile to my face. Daddy is finally finished and I'm all yours again. To my wife Heather, there are no words to describe what you mean to me. Thank you for all your love and support. I would not have been able to accomplish this or anything else without your understanding and patience. I look forward to our "normal" life again.

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CHAPTER 1: Introduction

1.1 Background

The Marine Corps Vision and Strategy 2025 [1] clearly details the Commandant's vision of the future Corps and describes his plan for creating the Marine Corps of 2025. Two important facets of this vision state the Marine Corps will deploy forward with relevant and timely capabilities and will be lean, agile, and adaptable. As part of this vision, the Deputy Commandant for Aviation has outlined goals to ensure the Aviation Combat Element (ACE) of the Marine Corps is aligned with Strategy 2025. Two of these goals are : (1) execute the planned Type/Model/Series transition strategies from the legacy platforms to the next generation platforms, and (2) improve warfighting integration by developing new concepts of operations to leverage our transformational systems.

To support these goals, the Marine Corps has pursued developments with unmanned aerial vehicles to increase the force-multiplying capabilities that these enhanced, multispectral (Electro-Optical/Infrared and Synthetic Aperture Radar) systems bring to the fight. Newly emergent concepts for unmanned aerial systems (UASs) employment will continue to enhance and extend the lethal and nonlethal capabilities of the Marine Air Ground Task Force (MAGTF). Joint Force Commanders will attain new levels of battlespace command and control and situational awareness by applying these newly emergent concepts.

A Concept of Operations (CONOPS) for the United States Marine Corps Unmanned Aircraft Systems, Family of Systems (FoS) [2] was developed to provide fundamental guidance for initial concepts, tactics, techniques, and procedures (TTPs) in order to meet the need of persistent Intelligence, Surveillance, and Reconaissance (ISR) on today's battlefield. As part of this CONOPS, three groups of unmanned aerial vehicles (UAVs) have been identified for employment by the USMC. They are Group 1, Group 3, and Group 4 systems.

Previous studies examined the interactions of UAVs amongst themselves in the context of target acquisition and engagement. The Navy is studying future applications and use of UAVs. This is highlighted by the Chief of Naval Operations (CNO) most recent Strategic Studies Group (SSG) XXVIII study on autonomous systems, entitled "The Unmanned Imperative." Specifically, the SSG was tasked to show how unmanned and manned systems interact and to optimize the com-

mand and control structure to better integrate unmanned naval assets with manned systems. The SSG believes this integration will allow the Naval services to overcome the challenges of the 21st century. In order to accomplish this, UAVs need to become more capable. Future use of UAVs will require them to be distributed globally, dispersed geographically, and have disaggregated functionality. Global distribution allows the commander to gain regional knowledge through persistent ISR. Geographical dispersion provides for greater battlespace awareness. Disaggregated functionality refers to tailored functions and capabilities based on mission need.

One of the critical capabilities of the UAV is autonomy. Autonomous systems can be thought of as possessing different “levels of autonomy” with some degree of human interaction combined with machine automation. Future CONOPS for all services will increasingly rely on this capability in some form, as many current UAVs, such as the Global Hawk, already operate with some degree of autonomy. A high level of automation will be required for future concepts that include large numbers of UAVs. In many large-scale operations where high numbers of UAVs may operate, the ability to self-coordinate may be needed due to the increased difficulty for operators to control multiple teams of UAVs.

However, there is a pitfall if the number of UAVs and their uses are increased without viewing them as part of an overall distributed force. Many unseen and unexploited opportunities for the use of these systems may be missed. Thus, it is important that these systems be utilized in such a way as to maximize the integration of unmanned and manned systems. Studying the integration and future employment options among UAVs and the interdiction teams they are tasked to support is just a first step in this process. If ground interdiction teams are augmented with an organic tracking capability (the ability to track targets on their own) in the form of a man-portable UAV, the potential exists to more rapidly acquire and track a target, which would allow the surveyor UAV to be released from tracking and return to its primary mission of ISR and target acquisition. It is believed the natural result of this interaction would be an increase in the number of targets acquired and captured during interdiction missions.

1.1.1 Overview of USMC UAV Family of Systems (FOS)

The essence of the USMC FOS is to provide the MAGTF with dedicated operational capabilities focused on battlespace awareness and force application while enabling enhanced command and control (C2) throughout the range of diverse military operations. In order to accomplish this, the Marine Corps will need to acquire significant numbers of smaller UAVs that will be organic to the ground combat elements table of equipment. These smaller UAVs will become part of

UAS Category	Max Gross Takeoff Weight	Normal Operating Altitude (Ft)	Airspeed	Representative UAS
Group 1	< 20 pounds	< 1200 AGL	<100 Kts	Wasp, Raven B
Group 2	21-55 pounds	< 3500 AGL	< 250 Kts	Scan Eagle
Group 3	< 1320 pounds	<18,000 MSL		RQ-7 Shadow
Group 4	> 1320 pounds		Any Airspeed	RQ-9 Reaper
Group 5		> 18,000 MSL		RQ-4 Global Hawk

Table 1.1: Joint UAS Category

the different "Groups" of UASs within the Marine Corps based on their capabilities. The group definitions have been categorized by the Joint UAS Center of Excellence based on weight, operating altitude, and airspeed (see Table 1.1). The greater these attributes, the higher the group number. Within the Marine Corps, Group 1 systems are micro and small UAVs, Group 3 systems are small tactical UAS (STUAS), and Group 4 systems are Marine Corps tactical UASs (MCTUAS). The Marine Corps currently does not have a Group 2 UAS requirement.

Group 1 systems include the RQ-11B Raven and Wasp. Wasp is organic to the infantry company and employed at the platoon or squad level. It is designed to be a small, rugged, man-portable system for employment at the tactical unit level for ISR missions. The Raven is organic to the infantry, artillery, armor, light reconnaissance, and amphibious assault battalions and employed at the company or battery level. It provides the company commander with enhanced situational awareness and observation of targets beyond the company's line of sight (LOS). It is larger than Wasp; however, both systems utilize common control stations and thus operation of these systems is similar. These systems are designed for close-in reconnaissance, surveillance, and target acquisition in support of infantry squads, platoons, companies, and battalions.

Group 3 systems are designed to be simple, transportable and rugged, yet capable of producing actionable intelligence for the maneuver commander. Group 3 systems will provide dedicated UAV support at the battalion level. Each system will have the following capabilities: electro-optical/infrared (EO/IR) sensors, integrated IR marker and laser range finder/designator, and communication relay packages. These systems are designed to be shipboard compatible with an unobstructed LOS operating radius of approximately fifty nautical miles (NM), and operate up to altitudes of 15,000 feet for extended periods of up to ten hours. Group 3 UAVs will be assigned to the Marine Unmanned Aerial Vehicle Squadrons (VMU) within the Marine Aircraft Wing (MAW).

Group 4 missions are currently performed by a Group 3 system according to the definition. The future Group 4 system will be the MAGTF's long-range, high-speed UAV with mission

sets that include C2, ISR, communication relay, target acquisition and marking, and precision strike. This system would be employed at the Marine Expeditionary Brigade (MEB) or Marine Expeditionary Force (MEF) levels. This platform may have future missions of performing the role of a cargo UAV or as an electronic warfare (EW) platform.

1.1.2 Future Vision of the USMC UAV FOS

> The UAS FoS provides the Marine Air-Ground Task Force (MAGTF) and its subordinate units dedicated operational and tactical, interoperable, integrated and tailored Battlespace Awareness and Force Application capabilities while enabling enhanced Command, Control, and Communications throughout the range of military operations. USMC UAV perform key roles in all Six Functions of Marine Aviation: Aerial Reconnaissance, Electronic Warfare (EW), Offensive Air Support (OAS), Assault Support, Anti-air Warfare (AAW), and Control of Aircraft and Missiles. [2]

The above statement is a sign of the future employment of UAVs within the Marine Corps. UAVs will be expected to perform and succeed in the six functions of Marine Aviation. Currently, with the exception of aerial reconnaissance, the six functions are performed by manned fixed and rotary wing aircraft. The vision is designed to not only save lives, but to provide for a high degree of interoperability among these systems and ground units to accomplish the mission. Some of these future concepts include Cargo UAS, Casualty Evacuation (CASEVAC) UAS, Manned-Unmanned Teaming (MUT), Unmanned Combat Air System (UCAS), cross cueing (adding information about a target of interest), and intelligence fusion (combing all information about a target).

Cargo UAS was envisioned as a need to reduce the number of convoys that are exposed to the improvised explosive device (IED) threat. By utilizing UASs for logistic support, potential IED attacks can be avoided and resupply can happen much more quickly, due to direct routing of the UAV and its speed. In a similar manner, UASs can be utilized to evacuate casualties from the combat zone and deliver them to field hospitals throughout the AO. MUT is the focus of this thesis and will be discussed in detail throughout. UCAS is envisioned to reduce the need to send manned aircraft into hostile areas. These UAVs will be able to deliver the same precision weapons as manned aircraft. They will also be smaller, lighter, and stealthier than

manned aircraft, thus reducing their radar cross-section and vulnerability to detection by enemy radar. This low observability translates into fewer fatalities in the combat zone. Cross cueing and intelligence fusion are concepts that are being practiced today but with the development of new technologies, these capabilities will become even more powerful. A real-time, fused intelligence picture will allow the analyst and warfighter to distinguish targets in cluttered, urban environments more easily, thereby increasing the likelihood of overall mission success.

With many of these concepts in mind, we will examine a small part of the future requirements in this thesis. We will seek to examine MUT, specifically Group 1 and Group 3 interactions with a quick reaction force (QRF) or interdiction team, to aid in the development of a CONOPS for UAS employment as described in the next section.

1.2 Problem Statement

The Situational Awareness for Surveillance and Interdiction Operations (SASIO) software provides an analysis tool and is designed to study mission characteristics and performance involving surveillance assets such as UAVs in conjunction with interdiction assets such as ground-based QRF teams. We will examine different teaming strategies and coordination measures between searching and interdicting assets in order to study the effectiveness of the interdictor possessing an organic, tracker UAV. The team's effectiveness is measured by the number of successful interdictions, i.e., detection, interception, and capture, of targets of interest.

Currently, there is a one-way flow of information, in that a ground unit may request an airborne asset to assist with its mission, but they do not have direct control over that asset. It is either piloted remotely from the Tactical Operations Center (TOC) or by aircrew of a fixed or rotary wing aircraft. As UAVs become more prevalent on the battlefield, ground forces will have to increasingly rely on them for ISR as well as target marking, overwatch operations, and perhaps even enemy engagement. There exists a need within all services for new or better TTPs and CONOPS for effectively teaming these ground units with organic UAVs.

The objective of this research is to quantify the benefit or penalty of an additional UAV asset in the context of the overall surveillance and interdiction operation using the SASIO model.

1.3 Research Questions

The objectives of this thesis research are guided by the following research questions:

- Is it better for an interdiction team to possess an organic "augmented tracking" capability in the context of time to intercept and number of targets captured?
- What are the significant factors that produce teaming strategies that result in the greatest number of hostile targets captured?

1.4 Literature Review

As UAVs become integrated on the battlefield, it is increasingly important to operate them in a highly efficient manner. Many concepts apply to future UAV operations. One concept is the efficient routing of UAVs in the Area of Operations (AO). Efficient routing needs to take into account terrain, mission, search pattern, number of targets, and the network structure of the AO. This concept has been studied in [3], where the authors developed a decision support tool utilizing a dynamic program that provides efficient search routes for multiple UAVs searching for multiple targets on a known graph of nodes and arcs. This problem was extended to the study of path planning for multiple UAVs [4]. In this study, the authors addressed the problem of generating feasible routes for multiple UAVs in a target rich environment. An anytime algorithm was developed using particle swarm optimization that results in routes whose quality increases with an increase in the computation time.

A second concept of UAV employment is that of sensing or target acquisition. Two significant factors that affect sensing are the probability that a target exists at a given location and the probability of the UAV seeing and identifying a target. One can use the number of hostile targets identified as a measure of effectiveness (MOE) for a given employment strategy. [5] investigated the value of predictive target assignment as a function of the number of unknown targets and number of UAVs. Target neutralization time (i.e., the time needed to neutralize targets) and total mission time (i.e., the time needed to destroy all targets) were the MOEs used. It was found that utilizing a prediction algorithm for target locations helped the cooperative UAV teams locate targets. As targets were located, they were stored in a database used by the UAV team to update target knowledge and thus update the prediction algorithm. As the target database increased, the predictions improved. In this study, the nominal density of targets within the AO will be known *a priori* and we will utilize different search algorithms as factors for our MOE. [6] studied the value of utilizing probabilistic information about reports of object detections and incorporated this information into a database that includes probabilities of an object's existence as well as probabilities of its location. This aids in the discrimination of false and real objects.

A natural extension of UAV teaming is the concept of MUT. MUT is a concept that takes advantage of a UAV's ability to detect targets and a ground team's ability to interdict those targets. It is precisely this concept that we study in this thesis. An integer linear program was developed to optimize the employment and deployment of UAVs integrated with Special Forces [7]. The goal of this model was to assist commanders in determining suitable locations for mobile control centers (MCC) and ground control units (GCU) as well as optimizing the search areas for the UAVs. The model resulted in 50% more target detections than manual plans generated by experienced commanders.

In order for success on the battlefield, UASs cannot be limited to operate in isolation. There must exist a level of coordination and integration with ground units. This problem was studied in an attempt to quantify the benefit of small, hand-launched UAVs as border patrol agents attempted to classify and capture illegal aliens at border crossing sites [8]. The MOEs used for this study were the number of illegal immigrants classified and captured and the number of smugglers classified and captured. This simulation study found there was an increase in correct classifications and captures with the aid of these UAVs.

Utilizing similar methodologies as the works above, we determine the benefit or penalty to interdiction efforts by the addition of an organic UAV capability for a single interdiction team when used in conjunction with a surveyor UAV. We measure the number of targets captured for a given AO size and target set. Target locations are not be known *a priori* and we do not utilize a predictive algorithm for target locations. Specifically, we use the number of targets captured and the time to capture as our MOEs. These results then have the potential to affect future CONOPS for the integration of UAVs with ground combat elements. Results of our simulation contribute to the development of a decision support tool that can aid the Commander as he determines which targets to interdict based on which presents the highest priority.

The remainder of this thesis is organized as follows. In Chapter II, presents the overall scenario to include a description of the problem domain. In this chapter, we also discuss constraints, assumptions and present the simulation model formulation. Chapter III discusses the experimental design used and presents a thorough discussion of factors, levels, response variables will also be presented. Chapter IV provides the analysis of the design and any insights gained from the simulation. Chapter V reports the conclusions and provide any recommendations that can be incorporated into future CONOPS as well as future model implementation.

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CHAPTER 2:
Model Formulation

This chapter will discuss the SASIO simulation model and its operational context. We begin with a general model overview followed by a discussion of the three core components: the theater, the scenario, and the task force. Each component presents the various characteristics and any entities it possesses and discuss the motion models that govern the entities.

2.1 Operational Context

The simulation environment possesses an Area of Interest (AOI) in which QRF teams are located at a FOB with the mission of interdicting and capturing hostile targets. Vehicle mounted QRFs will be restricted to the existing road networks. Foot mobile QRFs are not restricted to the road networks and although terrain often dictates ease of travel, for this thesis, terrain will not be a factor. The QRF can travel either by foot or vehicle (e.g., HMMWV) to the target location. The QRF will remain at the FOB until it receives a mission.

Airborne assets include a surveyor UAV that will perform ISR within the AOI. This UAV will utilize one of three specified search patterns to determine which provides the most target detections. Missions will be generated from reports sent to the FOB by the surveyor. After the report is generated surveyor can perform one of two missions. First, it can continue to search for additional targets. Alternatively, it can transition to a tracking mode, updating target action and location in the form of additional reports to the QRF. Once the QRF arrives at the target location, the surveyor will be released back to its search mission.

The QRF has the ability to have a tracker UAV assigned to it as an organic asset. Launched by the QRF when the surveyor issues a report, the tracker will proceed to the last known target location. If the surveyor is in tracking mode, the tracker will conduct a target handoff, once it has positively identified the target, releasing the surveyor to its search mission.

2.2 Overview of the Model

SASIO is an agent based simulation model written in the Java programming language. Agent based modeling is used to study the interactions of autonomous agents in complex systems. These models are used to simulate the actions of multiple agents in an attempt to predict or re-create complex phenomena. Monte Carlo techniques can be used to introduce randomness

to the model. SASIO defines both agent and object modeling. “Agents” refer to friendly forces and “objects” refer to either neutral or hostile targets. SASIO is used to define and construct, for example, multiple search methods for agents, agent planning and interdiction behaviors, object motion models, and their respective interactions with the environment.

2.3 Theater Description

Within SASIO the theater describes the region in which all entities interact. The theater for this thesis will consist of a range of AOIs from 10×10 km to 100×100 km. Each AOI consists of 1 km $\times$ 1 km grid squares and represent any location where real-world operations are currently ongoing. The choice for this size grid square is consistent with standard unit of measure for charts, maps, and gridded reference graphics used by ground and air assets in the current theaters of operation.

Each AOI can be represented by an undirected graph with a corresponding symmetric adjacency matrix, which defines all connections in the network. We will define three adjacency matrices as follows:

$$\begin{gathered}\mathrm{G}_1 \text{ is a grid graph where } C = 100\\ \mathrm{G}_2 \text{ is a grid graph where } C = 2500\\ \mathrm{G}_3 \text{ is a grid graph where } C = 10,000\end{gathered}$$

where C denotes the number of cells within each AOI. Each graph has eight-point connectivity, meaning each cell, c, may be connected in the following manner, {NW, N, NE, E, SE, S, SW, W}. Edge cells are connected in the same manner but with fewer adjacent cells. The adjacency matrix takes the following form:

$$\mathrm{Adj}_{\mathrm{G_i}} = [\mathrm{a_{i,j}}]= \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & \cdots \\ 1 & 1 & 1 & 0 & 0 & \cdots \\ 0 & 1 & 1 & 1 & 0 & \cdots \\ 0 & 0 & 1 & 1 & 1 & \cdots \\ 0 & 0 & 0 & 1 & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}, \text{ where } \mathrm{a_{i,j}} = \begin{cases} 1 \text{ if connected by eight pt. connectivity} \\ 0, \text{ otherwise} \end{cases}$$

These AOIs can be thought of as abstractions or extensions of Camp Roberts in California (see Figure 2.1) where ongoing research and experimentation utilize UAVs and ground assets to study operationally relevant problems such as proposed in this thesis.

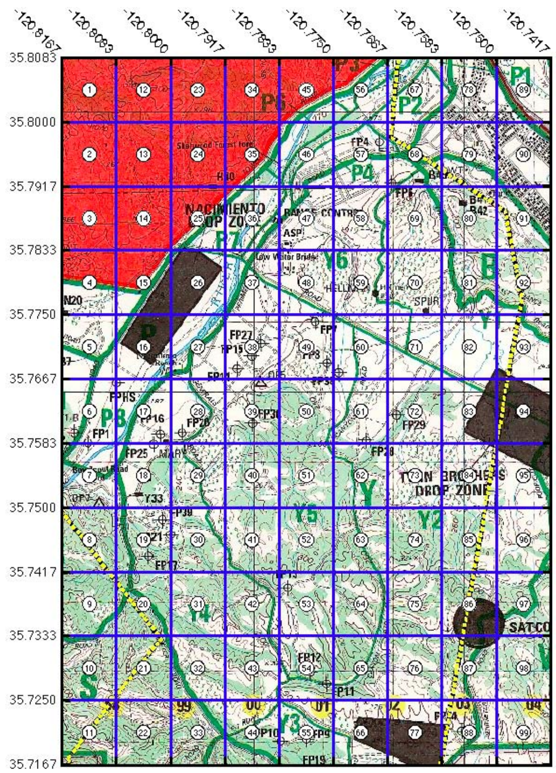


Figure 2.1: Camp Roberts Gridded Reference Graphic

2.4 Scenario Description

The scenario describes the number, movement, and prediction models of the red forces, known as objects. Objects in this thesis can either be targets or neutrals.

2.4.1 Object Placement Model

For this thesis, we will consider three separate object sets. We will let N be the number of objects and $N \in \{30, 75, 120\}$. The make up of the object set is a one to two ratio of hostile to neutral objects. For example, if N = 30, 10 objects will be targets and 20 will be neutral. Object placement is assumed independent which may result in more than one object being placed within a cell. Each object set will be placed within the AOI based on a probability map that is initialized at the start of the scenario with probabilities of an object being placed within a cell. We will define the probability using a uniform distribution across the entire theater in the following manner:

Let the discrete random variable X= the location of an object, where X = {1,2,3,...,C}, with probability distribution:

$P[X = c]$ = the probability that an object is located in cell c, then for uniform probabilities

$$P[X = c] = \frac{1}{C}$$

In order to generate the object locations, for each object we will generate a random number based on the number of cells in the AOI and then place the object at that cell location. For example,

$$R \sim U(1, C)$$

where recall that C is the number of cells in the AOI. This algorithm will continue until all objects have been assigned. Since all object locations are assumed independent, all assignments will follow the same uniform distribution.

2.4.2 Object Motion Model

In order to model object motion, we need to know the object's current location, all possible future locations, and the time step utilized to measure target velocity. Object motions are modeled as a discrete time Markov chain with a time step equal to one minute, i.e., $\Delta t = 1$. A discrete time Markov chain is specified by its transition matrix and its initial distribution. The objects' initial distribution, as described above, is given by

$$P[X = c] = \frac{1}{C} \text{ which can be written as } P[X_1] = P[X_2] = P[X_3] = ... = P[X_c] = \frac{1}{C}$$

Target locations can be determined by starting with their initial location given by the target placement model. The theater adjacency matrix represents all possible future locations for a target in a given cell. The adjacency matrix is a undirected graph that depicts all possible target flow from cell to cell. When the future locations are replaced by the probability of an object transitioning to that cell, the resulting matrix becomes the theater transition matrix, P. In order to determine the transition probabilities we use the following algorithm. This algorithm defines all one time step transition probabilities.

$\pi^{t+1} = P\pi^t$, where π^{t+1} is the probability of transitioning in one time step, P is the transition matrix, and π^t is the current location probability. This thesis will explore the Random Walk

motion model that can be generalized to different object motions. The object motions will be characterized by the transition probability possessed by the object and can range from a stationary target to a target that transitions at every time step.

Since the theater is represented by an undirected graph, the adjacency matrix is symmetric meaning if i is connected to j, then j is connected to i. A row of an adjacency matrix represents all cells adjacent to a given cell, i.e, if a cell j is adjacent to cell i, the $(i, j)-$entry in the adjacency matrix is one. The sum of this row is called the outdegree, which is defined as the sum of all arc tailpoints that emanate from that cell and connect to another cell. Formally

$$\text{outdegree}_i = \sum_{j=1}^{\mathrm{C}} a_{i,j}$$

Non-Uniform Random Walk Motion Model

In the non-uniform random walk model, the probability of transitioning to any adjacent cell is not described by a uniform distribution. Instead, the current location can be described as being self-important, meaning the target either wants to quickly leave the cell in which it is located or it would prefer to stay at the current location. The first case can be described as a fast random walk and the second as a slow random walk. In either case, this self-importance imparts a $\pi_{i,i}$, the self-transition probability for the current cell, that is different from its adjacent cells which is the cause of the non-uniformity. In order to find the transition probabilities for the remaining cells we need to perform the following calculation

$$\pi_{i,j} = \frac{1 - \pi_{i,i}}{\text{outdegree} - 1},\ j \neq i,\ j \in \text{Adj}_{G_i}$$

$$\pi_{i,j} = 0 \text{ if } j \notin \mathrm{Adj}_{\mathrm{G_i}}$$

Row entries for each c_{i} are determined in this manner. The resulting matrix is the transition matrix, P.

To take this argument one step further, since $\pi_{i,i}$ is a continuous factor, we see that as $\pi_{i,i}$ approaches the limit of 1, the transition probability to other cells approaches zero and thus we have the special case of the non-uniform random walk that describes a stationary target.

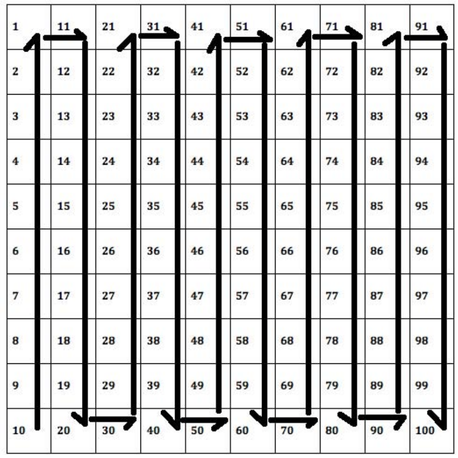


Figure 2.2: Lawnmower Search Pattern

It can also be shown that uniform random walk is a special case of the non-uniform random walk. In this case the transition probabilities are derived by the following equation

$$\pi_{i,j} = \frac{1}{\text{outdegree}}$$

that shows the object is equally likely to go to all adjacent cells and therefore has a transition matrix that is uniform for each discrete time step. Uniform walk will not be explicitly studied, since it falls within the continuum defined by the fast and slow random walk cases.

2.5 Task Force Description

The final part of SASIO is the taskforce that describes the blue force assets to include the surveyor, QRF, and the tracker UAV organic to the QRF. The taskforce describes all blue force agent capabilities and motion models.

2.5.1 Surveyor UAV

Search Pattern

The surveyor UAV represents a Group 3 system and will perform ISR in order to detect hostile targets within the AOI. It will fly one of three search patterns as directed by the operator. The possible patterns are lawnmower, spiral, and random walk (See Figure 2.2).

Identification

The surveyor is modeled with imperfect sensing capabilities and is the only Blue Force asset that must address this issue. The main characteristics of sensing are ρ, the false negative

identification probability and γ, the false positive identification probability. When the surveyor makes a detection there are four possible probabilities for target detection based on the sensing characteristics. These cases are (1) the probability of a correct negative identification (correctly observing no target present), 1-γ, (2) the probability of a false positive identification (incorrectly observing a target when none is present), γ, (3) the probability of a missed detection (incorrectly observing no target when one is present), ρ, and (4) the probability of correctly detecting a target, 1-ρ. These probabilities can be expressed using the following derivation:

Let X_c be a Bernoulli random variable describing target presence as defined below

$$X_c \triangleq \begin{cases} 0, & \text{no target present} \\ 1, & \text{at least one target present} \end{cases}$$

Let Y_c be a Bernoulli random variable describing target detection as defined below

$$Y_c \triangleq \begin{cases} 0, & \text{target not detected} \\ 1, & \text{target detected} \end{cases}$$

We can then say,

$$1 - \gamma \triangleq P\left[Y_c = 0 | X_c = 0\right]$$

$$\gamma \triangleq P\left[Y_c = 1 | X_c = 0\right]$$

$$\rho \triangleq P\left[Y_c = 0 | X_c = 1\right]$$

$$1 - \rho \triangleq P\left[Y_c = 1 | X_c = 1\right]$$

Surveyor Tracking Behavior

The surveyor is modeled as having one of two different capabilities. In the first case, the surveyor does not have a tracking capability. It executes its assigned search pattern, as per section 2.5.1 and upon making a detection issues a report containing the time and location of the detection. Since it has no tracking capability, the surveyor will continue its assigned search pattern

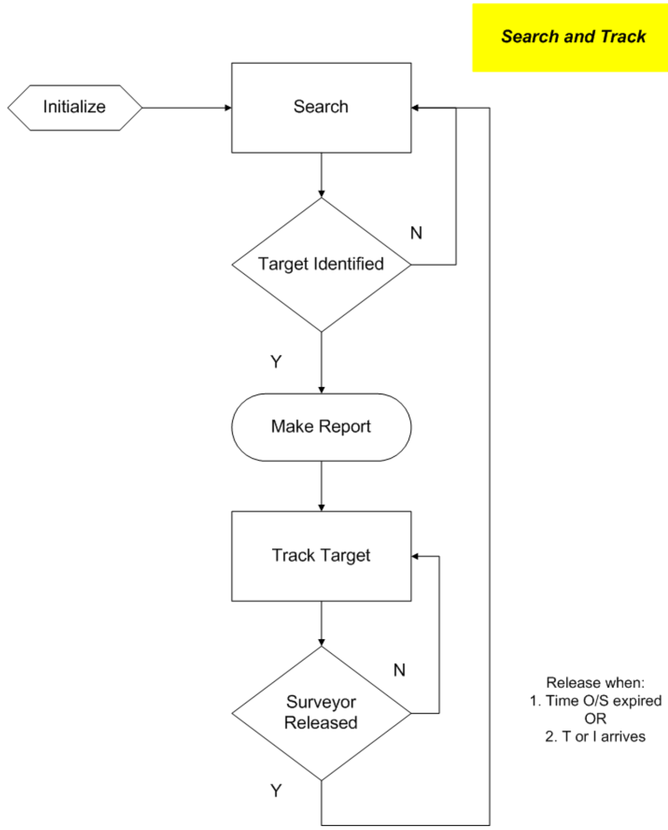


Figure 2.3: Surveyor with Tracking Capability Finite State Machine

and make additional reports as necessary. In the second case, the surveyor does possess a tracking capability. Upon detection of a target, it will issue a report but now transition into a tracking mode. The surveyor will continue to track the target until it released by the QRF or the tracking UAV at which time it will return to its search mission.

2.5.2 Interdiction Team (QRF)

Upon initialization of the simulation, the QRF is in a stationary mode, placed at the FOB location, and is listening for reports from the surveyor. The interdiction team will have two modes of transit: foot mobile and vehicle mounted. At each time step, the QRF listens for a report and if one is received it will begin its transit to the requested or goal location. Once the goal location is reached, the QRF will clear the target, and check for any unserviced reports from the surveyor. If there are unserviced reports, the QRF will transit to the new goal location. If there are no new reports, the QRF will transit back to the FOB. Once at the FOB, the QRF returns to stationary mode and begins listening for new unserviced reports. It is worth noting that the interdiction team brings two factors with three levels each to the simulation. The first is transit

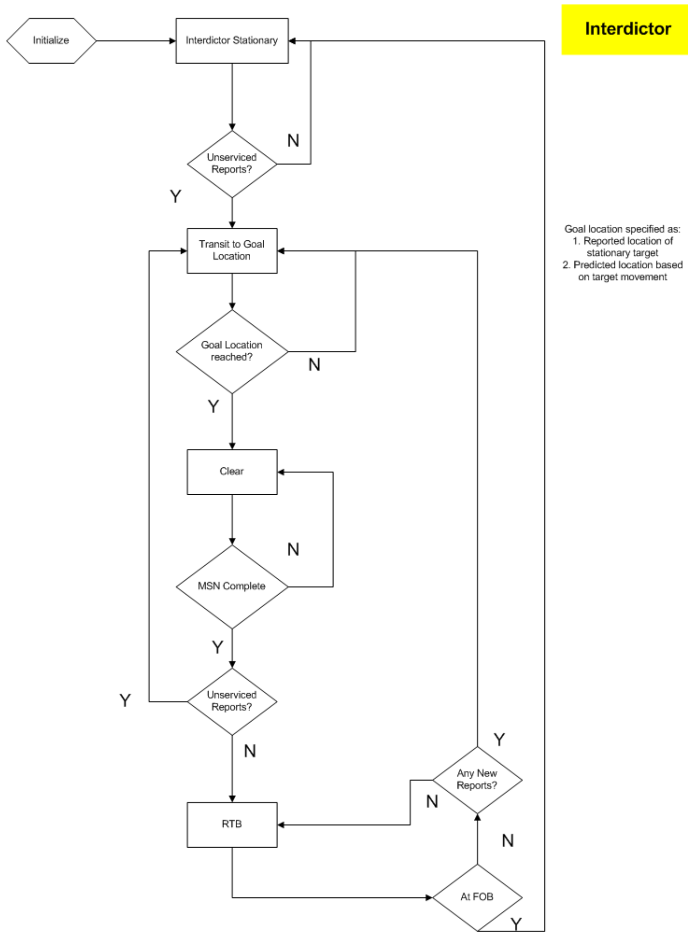


Figure 2.4: Interdiction Team Finite State Machine

time, which is a function of the mode of travel and the second is clear time, which will take on one of three values which will represent a delay at the goal location. This process will continue until either all targets are interdicted and cleared or the simulation ends.

The QRF may also have the added capability of an organic tracking UAV. The QRF model would now need to launch the tracker at the specified time or distance from the goal location. Also, release of the surveyor would be initiated by the tracker UAV once it is has received target handoff from the surveyor. Now when the QRF reaches the goal location, it will assume tracking responsibilities and release the tracker for any additional unserviced reports.

2.5.3 Tracker UAV

The tracker UAV represent a Group 1 system and will be initialized in a stationary mode co-located with the QRF and awaits tasking from the QRF. The tracker UAV represents a portable,

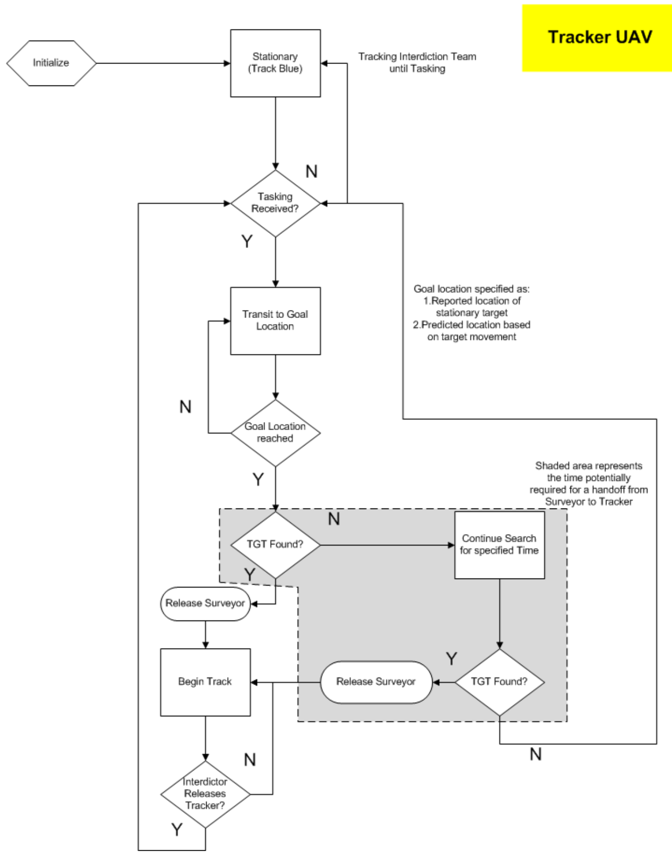


Figure 2.5: Tracker UAV Finite State Machine

hand-launched asset organic to the QRF. As the QRF transits to the goal location, it will launch the tracker at one of three specified distances from the goal location. These distances are one, three, and five cells from the goal location. The tracker velocity is 60 and 180 kilometers per hour which corresponds to approximately 35 and 100 knots. It is also assumed to have perfect sensing capability. Upon receipt of tasking, the tracker is launched by the QRF to begin its transit to the goal location. After receiving the target handoff from the surveyor, the tracker will release the surveyor back to its search mission and assume tracking responsibilities until arrival of the QRF. As the QRF arrives at the goal location, it will release the tracker for any additional unserviced reports if they exist. If there are none, then the tracker returns to the QRF.

CHAPTER 3:
Experimental Design

We use experimental design as the basis for determining the significant factors for the presented SASIO simulation model. Experimental design allows for estimating the effects of the input variables simultaneously where variation of the factors is present. Screening experiments allow the experimenter to vary factors in such a way that the most significant factors can be identified with respect to the response variables of interest, with as little experimental effort as possible. The SASIO software encapsulating the model is designed to utilize design of experiments (DOX) to study the aspects of UAVs' surveillance characteristics in conjunction with ground based interdiction teams with the overall goal of increasing the number of targets captured.

The model created for this thesis has several response variables of interest. The primary response variable is the number of targets captured. This is the metric by which we measure the benefit or penalty of the different teaming strategies. The second to be quantified is the percentage of time the surveyor UAV actually spends performing the search mission.

The remainder of this chapter introduces the response variables of interest as well as the factors to be used. A thorough explanation of the particular experimental design used will also be discussed. Finally, this chapter concludes with the analysis of the output from the simulation runs.

3.1 Response Variables

There are many factors and levels that will vary during this experiment. The model will be used to simulate the unpredictability of all entities in the AOI and thus will provide insights that demonstrate which factors have a significant effect on the response variables. We have two response variables for this simulation model and their descriptions follow below.

3.1.1 Percentage of Targets Cleared

This is the primary response variable that any commander will wish to know. The percent targets captured directly relates to how efficiently assets perform for a given teaming strategy. The higher this number, the more successful the teaming strategy. Insights can be gained on which QRF mobility type is preferred and if it is worth the effort to launch the tracker based on

Factor	Levels	Type	Description
Team Type	Surveyor	Categorical	UAV capabilities that are available to the QRF
	Surveyor/Tracking		
	Surveyor with Tracker		
Search Pattern	Random Walk	Categorical	patterns to be flown by Surveyor UAV only
	Lawnmower		
	Spiral		
Tracker Launch	[1, 3, 5]	Nominal	# cells from goal location
Interdictor Transit Time	[15, 2, 1]	Nominal	# time steps to traverse 1 cell
Tracker Speed	[1, 3]	Nominal	# cells traversed / time step
Surveyor Gamma (γ)	[0, 0.9]	Nominal	Constraint $\gamma + \rho \leq 0.9$
Surveyor Rho (ρ)	[0, 0.9]	Nominal	
Search Area	[100, 2500, 10000]	Nominal	# cells, C in the AOI
Interdictor Clear Time	[1, 11, 21]	Nominal	# time steps
Number of Objects	[30, 75, 120]	Categorical	1:2 target to neutral ratio
Object Motion	Slow Random Walk	Nominal	Dependent on self transition probabilities, $\pi_{i,i}$
	Fast Random Walk	Nominal	

Table 3.1: Factors and Levels

QRF distance to the target. This response will be obtained directly from the interdictor cleared list stored within SASIO.

3.1.2 Percentage of Time Surveyor UAV Performs Search

This secondary response relates to the percent targets cleared. Of interest is how augmented tracking affects this response when the surveyor possesses a tracking capability. This response will be obtained by subtracting the surveyors tracking time from the total simulation time and then dividing by total simulation time. The purpose behind the different teaming strategies is to identify the strategy that results in the highest percent of targets captured per simulation run.

3.2 Factors and Levels

The following factors and levels to be investigated in this thesis are listed in Table 3.1.

Each factor represents a characteristic of the entities in the simulation and represents a particular value the factor can take during the course of the mission. Each factor and its expected impact to the results follow.

3.2.1 Team Type

Description

The Team Type is the main focus of this thesis. Team Type is the ultimate decision a commander will need to make in order to achieve his objectives. The first strategy utilizes a surveyor UAV only with no tracking capability. The second strategy represents a surveyor UAV that has tracking capabilities. The third strategy will utilize the surveyor but it will be augmented with an additional tracking UAV, organic to the QRF. This factor can take on three discrete levels and is therefore categorical.

Predicted Impact

We predict the augmented tracking provided by the tracker UAV will allow the surveyor to spend more time in its primary mission of reconnaissance. As a result, more targets should be identified and captured during the course of the simulation. Thus, an increase in the primary and secondary response is expected.

3.2.2 Search Pattern

Description

Search pattern is also a categorical variable and will have three levels: lawnmower, spiral out, and random walk. With the exception of the random walk, each represents a predefined set of waypoints for the surveyor UAV to travel as it searches for targets. The search patterns will not be affected by intelligence related to target locations. UAVs will fly the specific pattern until a target is detected, at which time a report will be issued and the surveyor will either track the target until released by the QRF or it will continue to search depending on its capabilities and the current strategy.

Predicted Impact

The search patterns we will use make a difference if there are a large number of targets randomly clustered together where the UAV has the ability to find one right after another. If the targets are placed randomly far apart, then we do not anticipate the search pattern having much of an effect on the percent targets captured.

3.2.3 Tracker Launch

Description

The launch of the tracker UAV is modeled using three thresholds, representing the number of cells from the target when the tracker is launched. The three values are one, three, and five cells.

Predicted Impact

This factor when combined with the tracker speed will effect the amount of time the surveyor will spend conducting its primary mission of reconnaissance. The earlier the tracker can be launched and the faster it can arrive at the goal location, the sooner it can relieve the surveyor and thus return to its search mission.

3.2.4 Interdictor Transit Time

Description

These values will represent the number of time steps required to traverse from one cell to an adjacent cell. Each value simulates different modes of travel from a foot mobile QRF to a vehicle mounted QRF traveling on a road network with velocities ranging from 4kph to 60kph.

Predicted Impact

As the velocity of the QRF decreases more time will be required to transit to a goal location. This translates into more time the surveyor has to remain on station before being released by either the QRF or the tracker, which we predict will negatively effect the number of targets identified and captured.

3.2.5 Tracker Speed

Description

This factor represents the different velocities the tracker UAV may fly. We assume perfect sensing for the tracker so speed will not affect tracker γ and ρ. It has two levels, one and three, which represent the number of time steps required to traverse from one cell to the next cell en route to the target location. These levels are equivalent to 60 and 180kph.

Predicted Impact

Assuming surveyor will be released by the tracker, the quicker the tracker can arrive at the goal location to release the surveyor, the sooner the surveyor can return to its mission. This should lead to an increase in the percent targets captured and the total number of targets identified.

3.2.6 Sensor Characteristics

Description

Two continuous factors are used to represent the imperfect sensing capabilities of the surveyor UAV. γ (gamma) is the probability of having a false positive, which is identifying a target as

hostile when it is not. ρ (rho) is the probability of a false negative, which is classifying a target as friendly when it is in fact hostile.

Predicted Impact

While both γ and ρ can have a significant effect, γ is a greater concern due to the misclassification of a neutral as a target. The higher this misclassification rate, the more time the QRF will spend clearing objects that are not targets and thus as γ increases for the surveyor, we would expect to see the percent targets captured decrease.

3.2.7 Search Area

Description

The search area is a continuous factor based on AOIs composed of 1 km x 1 km grid squares. Varying this factor will also help quantify the benefit or penalty of the QRF having an organic UAV tracking capability.

Predicted Impact

An increase in search area should make it more difficult to locate targets. Therefore, we would expect to see a decrease in the percent targets captured as the size of the search area is increased.

3.2.8 Clear Time

Description

This factor represents the amount of time it takes for the QRF to actually interdict and capture a target. This factor takes on three levels as shown in Figure 3.2.

Predicted Impact

We expect that as the clearing time is increased fewer additional targets found by the surveyor will be interdicted and cleared by the QRF.

3.2.9 Number of Objects

Description

The number of objects in the AOI will take on three distinct values. The objects will be randomly placed throughout the AOI and will have no affect on the search pattern used by the surveyor or mode of travel of the QRF. The particular level represents a 1:2 ratio of targets to neutrals in the AOI. For example, if the number of objects equals 30, there are 10 targets and 20 neutrals in that target set.

Predicted Impact

As this factor is varied with different AOI sizes, we expect to see significant variation to the number of targets identified and therefore the percent targets captured.

3.3 Experimental Design

The choice of experimental design was developed to accommodate eleven input factors. This experiment constitutes a mixed-level design, for which the design matrix was created using the D-optimality criterion that results in a nearly orthogonal design. The result is nearly orthogonal because some correlation exists among the columns of the information matrix $[X'X]$. A D-optimal design attempts to minimize the variance of the model regression coefficients [9].

Factor screening is the process of systematically varying input factors in order to identify the factors that produce a significant change in the response variables. The screening experiment is used to estimate the magnitude and direction of individual factor effects as well as factor interaction effects on the response variable. As previously mentioned, we are using a D-optimal design for the screening experiment in an attempt to minimize the variance of the model regression coefficients. The D-optimal design minimizes the volume of the joint confidence region on the vector of regression coefficients by minimizing $|(X'X)^{-1}|$, which equates to minimizing the uncertainty of the regression coefficients.

Traditional screening experiments are conducted using only two levels of the factors, a low level and a high level. Center points are added to the design to check for non-linearity within the model and to reduce the variance in the center of the design space. The resulting design matrix is read into the SASIO model and the simulation conducted using the actual values as found in Table 3.1. The design matrix developed in JMP 8.0.1 [10] resulted in 102 design points including six center points.

In order to analyze the data, the actual values in Table 3.1 must be transformed to coded values that strips the units from any level and turns the result into a level that is dimensionless. This allows the magnitude of the model coefficients to be directly comparable and the effect of changing each design factor over a single unit is easily measured. Coded variables are effective for determining the relative size of factor effects and allow the experimenter to see the relative importance of the design factors. Output data is then analyzed in JMP but with the factor values converted to coded units of -1, 0, and 1 to represent the low, center point, and high levels respectively. There were some cases where we chose a third level that was not the exact

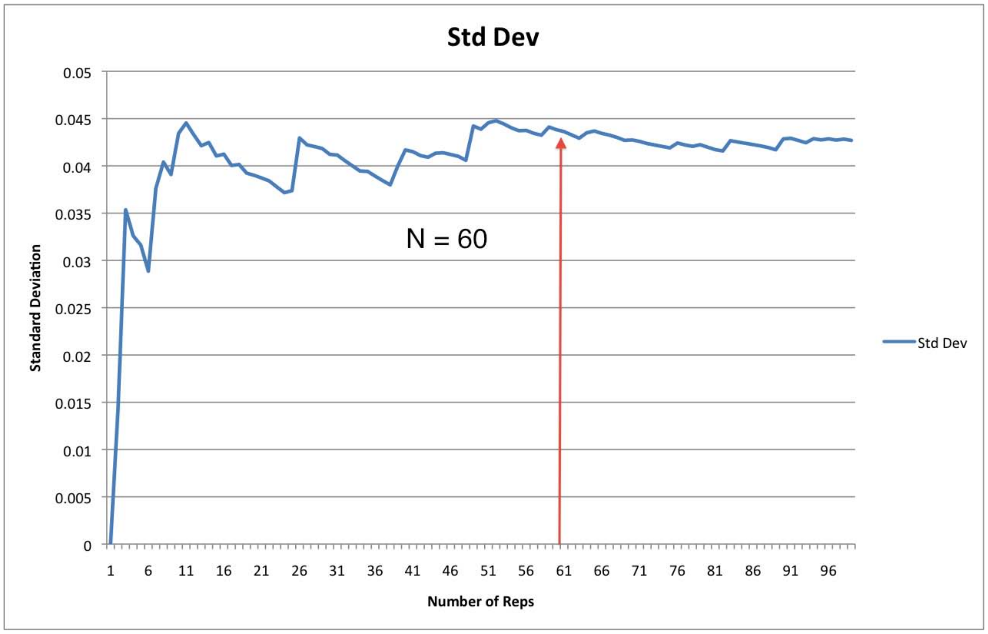


Figure 3.1: Asymptotic Standard Deviation

center point. This was done to more accurately represent the level as a real world value for the particular level. Actual values were converted to coded units using the following formula:

$$\text{coded value} = \frac{\text{Actual value} - (\text{Actual}_{\text{Low}} + \text{Actual}_{\text{High}})/2}{(\text{Actual}_{\text{High}} - \text{Actual}_{\text{Low}})/2}$$

3.4 Methods of Analysis

3.4.1 Asymptotic Variance

Through a study of the asymptotic variance, we determined 60 replications of each design point was adequate to gain insights from the simulation model, see Figure 3.1. We ran the model for one design point multiple times while varying the number of replications until the standard deviation of both response varibles stabilized. This occured at approximately 60 replications. We performed this analysis in order to determine the minimum number of runs per design point while being able to gain insights from the simulation with the goal of running the simulation on a tactical laptop in the field. The simulation can run from less than an hour to approximately six hours depending on the number of design points.

3.4.2 Multivariate Linear Regression

Multivariate linear regression can be used to determine what factors in the screening experiment have a significant effect on the response. In a linear regression model the response variable, y is related to predictor variables, x through the following relationship

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{1,2} x_1 x_2 + \cdots + \beta_n x_n + \varepsilon$$

The standard multivariate linear regression model tests the following hypothesis:

$\mathrm{H}_0 : \beta_0 = \beta_1 x_x = \beta_{1,2} x_{1,2} = \beta_n x_n = 0,$ where $n$is the number of coefficients

H_1 : at least one coefficient $\neq 0$

3.4.3 Logistic Regression

Logistic regression is used for the prediction of the probability of the occurrence of an event. The event we are interested in is the probability of a target being cleared. The number of targets cleared is a Bernoulli random variable that can take on the values of zero or one. Either the target is cleared or it is not. When a response variable is binary, the resulting shape of the response function is nonlinear [11]. This nonlinear function takes the form

$$logit = \frac{1}{1+\exp(-\boldsymbol{x'\beta})}$$

An examination of this function shows that it is easily linearized by using the logit transformation defined below as

$$\eta = \ln\left(\frac{P(x_i)}{1-P(x_i)}\right),\ \text{where } \eta \text{is the linear predictor of the response variable } y$$

By employing this transformation we are able to linearize the response variable and perform standard multivariate linear regression.

In order to determine the primary response variable, the mean number of targets was determined for each design point and then divided by the number of targets for that design point to attain the percent targets cleared. The resulting percent was transformed via the logit function to ensure the response variable values remained between zero and one and is shown below

$$\text{logit(percent targets cleared)} = \ln\left(\frac{\text{percent targets cleared}}{\text{1-percent targets cleared}}\right) = \boldsymbol{x\beta} + \varepsilon$$

CHAPTER 4:
Numerical Analysis

As mentioned in Chapter 3, screening experiments were performed to determine the significant factors that affect the two response variables: (1) percentage of targets cleared, and (2) the percentage of time the surveyor UAV performs its primary mission of search.

The first part of the analysis performed was to determine the effect of Tracker Launch and Tracker Speed only for the Team Type of Surveyor with Tracker. To accomplish this, we broke down Surveyor with Tracker into five separate factors each representing the high-low combinations and centerpoints of Tracker Launch and Tracker Speed. This was done to isolate the effects and because these effects are not present for the Surveyor only and Surveyor/Tracking Team Types. Table 4.1 shows how we broke down Surveyor with Tracker.

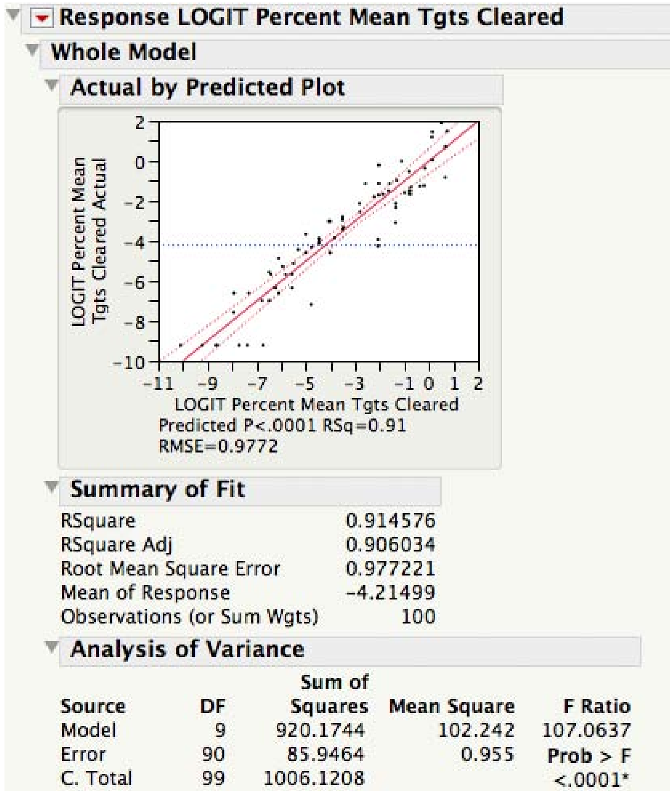
The analysis was performed omitting Tracker Launch and Tracker Speed. Performing the analysis in this way allowed for effects of Tracker Launch and Tracker Speed to be preserved for Surveyor with Tracker while at the same time being removed from the analysis in order to ensure those factors do not impact the Team Types where the Tracker is not part of the simulation model. The remainder of this chapter will discuss the results of the screening experiments.

4.1 Percentage of Targets Cleared

The initial regression analysis showed eight main and interaction effects were significant. Further analysis showed that an equally good model, in terms of R^2, could be achieved with only five main and interaction effects. The results are summarized in Figure 4.1.

Team Type	Tracker Launch Level	Tracker Speed Level
Surveyor with Tracker A	1	1
Surveyor with Tracker B	-1	-1
Surveyor with Tracker C	1	-1
Surveyor with Tracker D	-1	1
Surveyor with Tracker E	0	0

Table 4.1: New Team Type-Surveyor with Tracker A-E



RSquare	0.914576
RSquare Adj	0.906034
Root Mean Square Error	0.977221
Mean of Response	-4.21499
Observations (or Sum Wgts)	100

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	9	920.1744	102.242	107.0637
Error	90	85.9464	0.955	Prob > F
C. Total	99	1006.1208		<.0001*

Figure 4.1: Linear Regression model of LOGIT transformation of Percent Targets Cleared

Figure 4.2 lists the parameter estimates in order of lowest to highest p-value. The regressor with the largest coefficient is Search Area. As the search area is increased, a negative response in the percent of targets cleared is anticipated. Since our analysis was conducted using coded variables, we can obtain the odds ratio for a single unit increase in search area to be $e^{-2.56} = 0.077$, not taking into account the effects of the other factors. This odds ratio can be interpreted as the estimated increase or decrease in the Percentage of Targets Cleared [11] per unit increase on Search Area. Therefore as Search Area increases from its mid level to high level, the odds of success is approximately 8 out of 100. This model also shows that utilizing a team type comprising only a Surveyor asset with no tracking capability produces the least desireable results in terms of the response. The corresponding odds ratio is $e^{-2.37} = 0.09$, which equates to a reduction in the odds of success to 9 out of 100. A similar argument can be made for Interdictor Transit Time and False Negative Probability of detection.

The interaction of Interdictor Transit Time and Number of Objects is worth examining even though its effect is relatively small. Figure 4.3 shows that with a large number of objects, increasing the interdictor transit time still does not improve the percentage of targets cleared.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Search Area	-2.566751	0.100065	-25.65	<.0001*
New Team Type[Surveyor]	-2.371272	0.184337	-12.86	<.0001*
Interdictor Transit Time	-0.744327	0.101361	-7.34	<.0001*
False Neg Prob	-0.715261	0.106146	-6.74	<.0001*
New Team Type[Surveyor with Tracker B]	0.9453771	0.309938	3.05	0.0030*
Interdictor Transit Time*Number of Objects	-0.274924	0.100843	-2.73	0.0077*
New Team Type[Surveyor with Tracker D]	0.7168729	0.311846	2.30	0.0238*
New Team Type[Surveyor with Tracker C]	0.3268827	0.309746	1.06	0.2941
New Team Type[Surveyor with Tracker A]	0.0389965	0.310307	0.13	0.9003

Figure 4.2: Sorted Parameter Estimates of LOGIT Transformation of Percent Targets Cleared in Order of Significance

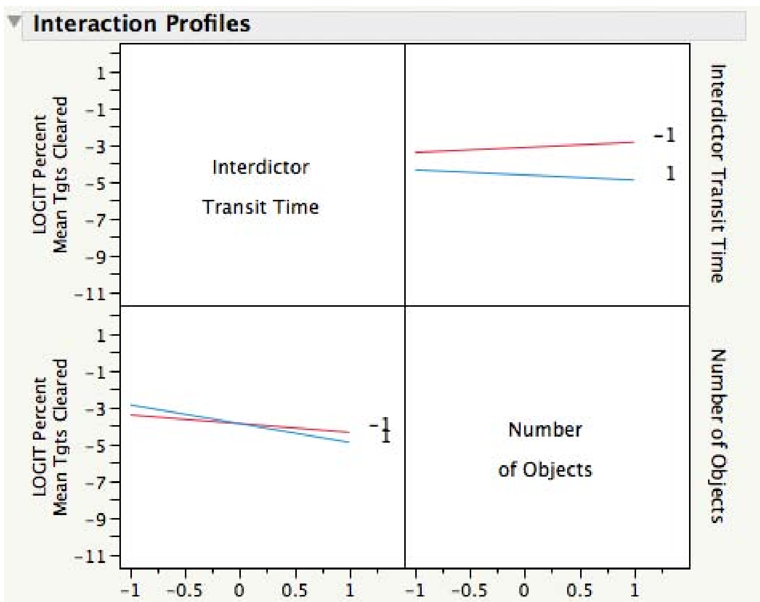


Figure 4.3: Interaction Profile showing the change in response as Search Area size interacts with New Team Type

The QRF is simply overwhelmed by the number of objects to interdict. This result supports the argument for more QRF or patrols if a target rich environment is anticipated.

Tukeys Least Squares Means Differences allows us to perform a multiple comparison of the means to determine if there is a significant difference among any pair of factors. Tukeys method then groups the mean responses that are not statistically different as seen in the crossletter report (Figure 4.4). Also shown is a plot showing the difference in the means between Team Types with a tracking capability and those without. We can see a significantly lower mean response for Surveyor when compared with Surveyor/Tracking and Surveyor with Tracking. This supports our conclusion that possessing a tracking capability will positively impact the response.

Level		Least Sq Mean
Surveyor with Tracker B	A	-2.742302
Surveyor with Tracker D	A	-2.970806
Surveyor/Tracking	A	-3.344536
Surveyor with Tracker C	A	-3.360797
Surveyor with Tracker A	A	-3.648683
Surveyor	B	-6.058951

Levels not connected by same letter are significantly different.

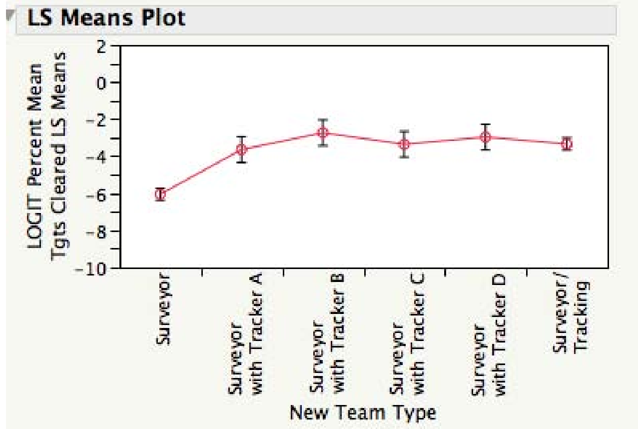


Figure 4.4: Tukeys Crossletter Report and Plot of the Least Squares Means showing New Team Type Grouped by Similar Means

4.1.1 Percentage of Targets Captured with Tracking Capability

After establishing that possessing a tracking capability is better than no tracking capability, we were interested in the significant effects when the Surveyor Team Type was not included in the model. For this analysis, all Surveyor data was removed. Initial results of the stepwise regression produced a good fit with 17 main and interaction effects. Further analysis illustrates that seven main and interaction effects is also satisfactory. Results are shown in Figures 4.5 and 4.6.

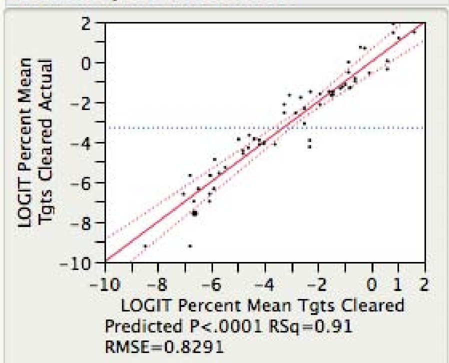
Figure 4.6 lists the significant factors from most to least influential for this model. Search Area has the greatest effect on the response. The odds ratio is $e^{-2.29} = 0.10$, which equates to a reduction in the odds of success to 10 out of 100 per unit increase of Search Area, which is very close that of the model with Team Type Surveyor included.

Interdictor Transit Time is the next factor in the list. This was an anticipated result as was the effect of the surveyor's sensor characteristics. Increasing the False Negative Probability, ρ, reduces the percentage of targets captured due to the increase in targets being misclassified as neutrals. An increase in the Number of Objects, coupled with other factors, increases the response simply because as the number of objects increases so does the number of targets.

Response LOGIT Percent Mean Tgts Cleared

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.913089
RSquare Adj	0.901304
Root Mean Square Error	0.829083
Mean of Response	-3.29737
Observations (or Sum Wgts)	68

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	8	426.07409	53.2593	77.4817
Error	59	40.55533	0.6874	Prob > F
C. Total	67	466.62942		<.0001*

Figure 4.5: Linear Regression Model of LOGIT Transformation of Percent Targets Captured

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Search Area	-2.296026	0.106584	-21.54	<.0001*
Interdictor Transit Time	-0.839092	0.106551	-7.88	<.0001*
False Neg Prob	-0.786552	0.128978	-6.10	<.0001*
Search Area*Number of Objects	0.4054962	0.114252	3.55	0.0008*
False Neg Prob*Number of Objects	0.3097635	0.108559	2.85	0.0060*
Search Pattern[Random Walk]*False Neg Prob	-0.400553	0.150251	-2.67	0.0099*
Search Pattern[Lawnmower]*False Neg Prob	0.3800016	0.158974	2.39	0.0200*
False Pos Prob	-0.292024	0.129502	-2.25	0.0279*

Figure 4.6: Sorted Parameter Estimates of LOGIT Transformation of Percent Targets Cleared in Order of Significance

Of greater interest is the lack of any effect from either Tracker Launch or Tracker Speed. In neither model do these factors have an effect. Tracker capabilities were modeled using the Raven UAV, the USMC's Group I UAV. Further study is required to determine if a Tracker with greater capabilities would have a greater effect on the response variable.

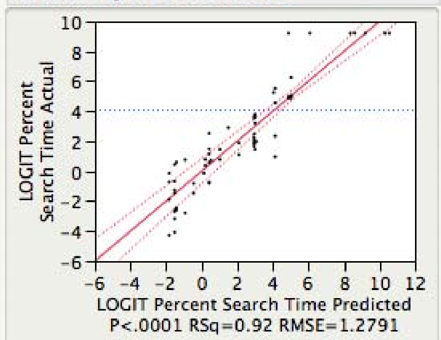
4.2 Percentage of Time Surveyor UAV Performs Search

Performing an initial analysis of search time yields a model with 10 main and interaction effects. Further analysis yields a model with only four main and interaction effects and R^2 of 0.92 and

Response LOGIT Percent Search Time

Whole Model

Actual by Predicted Plot



Summary of Fit

RSquare	0.924418
RSquare Adj	0.913993
Root Mean Square Error	1.279075
Mean of Response	4.088854
Observations (or Sum Wgts)	100

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	1740.8602	145.072	88.6728
Error	87	142.3349	1.636	Prob > F
C. Total	99	1883.1951		<.0001*

Figure 4.7: Linear Regression Model of LOGIT transformation of Percent Time Search

Sorted Parameter Estimates

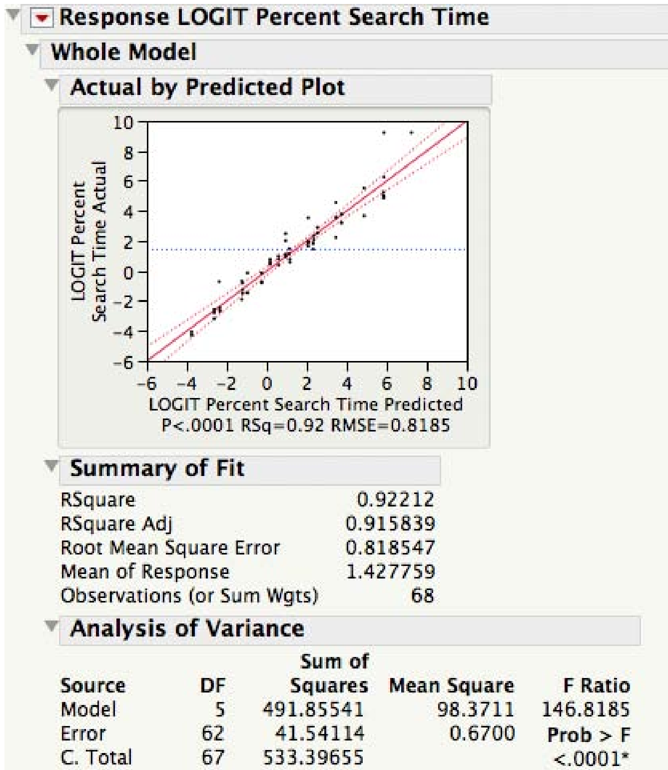
Term	Estimate	Std Error	t Ratio	Prob>|t|
New Team Type[Surveyor]	6.3044172	0.241679	26.09	<.0001*
Search Area	1.7617465	0.162107	10.87	<.0001*
New Team Type[Surveyor]*Search Area	-1.88394	0.245388	-7.68	<.0001*
False Neg Prob	0.9745043	0.143901	6.77	<.0001*
New Team Type[Surveyor with Tracker C]	-2.037017	0.414664	-4.91	<.0001*
New Team Type[Surveyor with Tracker B]	-1.340732	0.405956	-3.30	0.0014*
New Team Type[Surveyor with Tracker D]	-1.133776	0.403812	-2.81	0.0062*
New Team Type[Surveyor with Tracker A]*Search Area	0.527073	0.414751	1.27	0.2072
New Team Type[Surveyor with Tracker B]*Search Area	0.4872861	0.409871	1.19	0.2377
New Team Type[Surveyor with Tracker A]	-0.330549	0.414664	-0.80	0.4275
New Team Type[Surveyor with Tracker D]*Search Area	0.2000334	0.409376	0.49	0.6263
New Team Type[Surveyor with Tracker C]*Search Area	0.196679	0.414881	0.47	0.6366

Figure 4.8: Sorted Parameter Estimates of LOGIT transformation of Percent Time Search in order of significance

adjusted R^2 of 0.91. The results are shown in Figure 4.7.

The results shown in Figures 4.7 and 4.8 show that we would reject the null hypothesis in favor of the alternative at any reasonable confidence level.

When all Team Types are included in the model, the predictive power of this model can be skewed by the Surveyor team type as shown in Figure 4.8. This is due to Surveyor having no tracking capability, which therefore ensures that it will spend the entire duration of the mission



Summary of Fit	
RSquare	0.92212
RSquare Adj	0.915839
Root Mean Square Error	0.818547
Mean of Response	1.427759
Observations (or Sum Wgts)	68

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	491.85541	98.3711	146.8185
Error	62	41.54114	0.6700	Prob > F
C. Total	67	533.39655		<.0001*

Figure 4.9: Linear Regression Model of LOGIT Percent Time Search

searching. Of additional interest is how Percent Search Time responds when the team types include a tracking capability, which is described in the following section.

4.2.1 Surveyor Search Time Percentage with a Tracking Capability

The initial analysis excluding the Surveyor only Team Type yielded a model with eight main and interaction effects. Further analysis showed that a model with only five factors produced an R^2 of 0.92 and an adjusted R^2 of 0.91. These results are summarized in Figure 4.9 and 4.10.

The sorted parameter estimates in this case show that the greatest effect is due to the Search Area. The odds ratio is $e^{-2.34} = 0.09$ which is a reduction in the odds of success to 9 out of 100 for each unit increase in Search Area size. Next, the False Negative Probability increases the search time due to an increase of the misclassification rate of targets as neutrals. This leads to Surveyor not tracking and thus increases the search time at the expense of targets captured. The next factor with the greatest effect is the Number of Objects. As the Number of Objects increases, the percentage of time the Surveyor searches will decrease due to the tracking time involved with each additional target found. False Positive Probability has the opposite effect

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Search Area	2.3492065	0.102521	22.91	<.0001*
False Neg Prob	1.7504826	0.127077	13.77	<.0001*
Number of Objects	-0.707536	0.102929	-6.87	<.0001*
Interdictor Transit Time*Search Area	0.6905477	0.102882	6.71	<.0001*
Flase Pos Prob*False Neg Prob	0.5635082	0.124617	4.52	<.0001*

Figure 4.10: Sorted Parameter Estimates of LOGIT Percent Time Search in order of significance

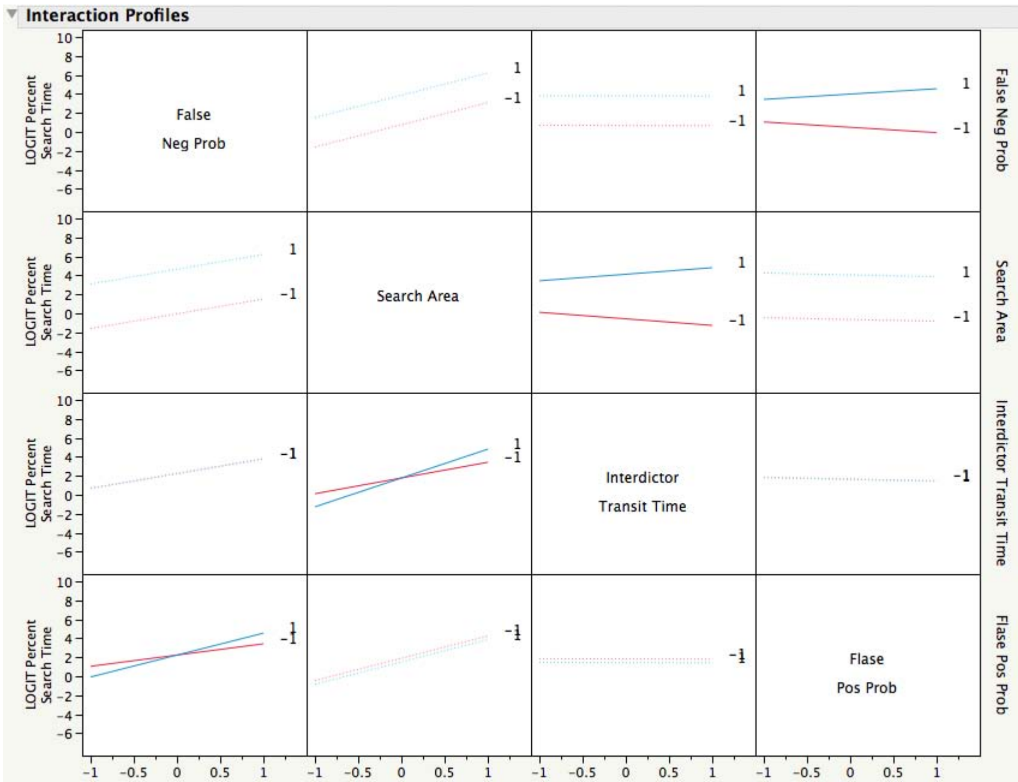


Figure 4.11: Interaction Plots of Search without Surveyor Team Type

of False Negative Probability. As the False Positive Probability rate increases, Surveyor spends less time searching and more tracking neutral targets.

The interaction of Interdictor Transit Time and Search Area provides an interesting insight to this model as depicted in Figure 4.11.

An analysis of the interactions without the Surveyor Team Type is shown in Figure 4.11. This plot shows that while Search Area is at its high level (1), as the Interdictor Transit Time decreases (faster interdictor speed) the percentage search time decreases. At an Interdictor Transit Time of 15kph, its high level, the Search Area is so large that the Surveyor spends a longer time tracking than searching while the QRF is en route to the target location. At the low level

Search Pattern	Lawnmower
Tracker Launch	3
Interdictor Transit Time	1
Tracker Speed	3
False Positive Probability	0.3
False Negative Probability	0.3
Clear Time	20
Number of Objects	120
Object Motion	SlowRW

Table 4.2: Factor Levels used for Sensitivity Analysis

of Search Area, as Interdictor Transit Time decreases, the percentage search time actually increases. Due to the small size of the AOI at the low level, the interdictor is able to get to the goal location very quickly releasing the surveyor to continue its search mission in less time than in a larger AOI.

4.3 Sensitivity Analysis

Having determined that Search Area and Team Type have the largest effect on both response variables, we performed sensitivity analysis to quantify those effects. All factors were held constant with the exception of Team Type and Search Area. The factor values used are shown in Table 4.2

Both were varied across their respective ranges or categories that resulted in eighteen design points. The results shown in Figure 4.12 clearly indicate that having a tracking capability is better than no tracking capability. Holding all factors fixed with the exception of Search Area and Team Type indicates that as the search area is increased the percentage of targets cleared decreases.

Figure 4.13 also shows that as the Search area increases the search time of the Surveyor also increases.

It is interesting to note that while possessing a tracking capability is superior to no tracking capability, there is no statistical difference between the Team Types Surveyor/Tracking and Surveyor with Tracker. For both MOEs, it is the tracking effect that affects the MOE, not the tracking Team Type. As mentioned in Section 4.2.1, the limiting factor for these Team Types is the Interdictor Transit Time. Regardless of how the tracking capability is employed, the number of targets cleared in a given mission time is limited by how many targets the interdictor

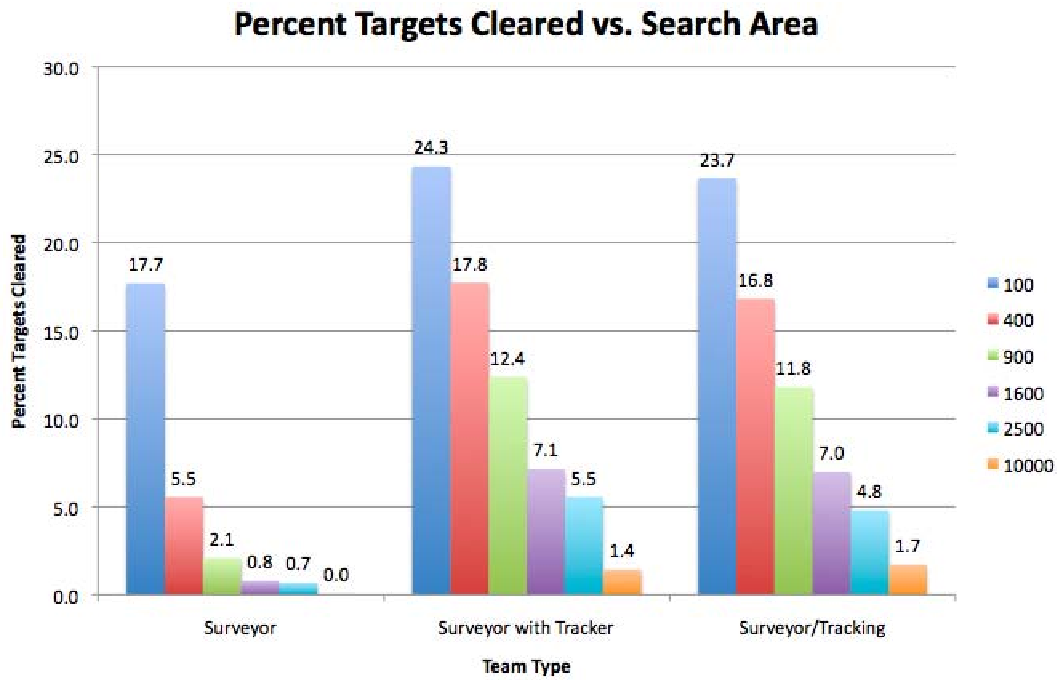


Figure 4.12: Average Percent Targets Cleared vs. Search Area Size

can actually get to during the mission.

4.4 Analysis Summary

Based on the screening for each response, in all cases the factor with the greatest effect is the Team Type and Search Area. Surveyor Team Type produces a low response for the Percentage of Targets cleared due to the lack of tracking capability. As shown in Figure 4.13, possessing a tracking capability reduced the amount of time the Surveyor searches as it performs its secondary mission of track rather than search. Neither of these conclusions indicate that the QRF having an organic Tracker UAV is a valuable asset. The sensitivity analysis performed only on the Team Types with a tracking capability produced similar results. For these team types, Tracker Launch and Tracker Speed produced no significant effects for either response variable. In order to produce an effect in either response variable from Tracker Launch and Speed, we would recommend performing the analysis with a Tracker UAV of greater capability.

We have also discovered that the hard part of target capture is not the interdiction of targets but the search for them which relates directly to the Search Area size. How we search and the assets available continue be the main limiting factors in target acquisition. The number of team types and assets available is an area for future study to help determine an acceptable size AOI

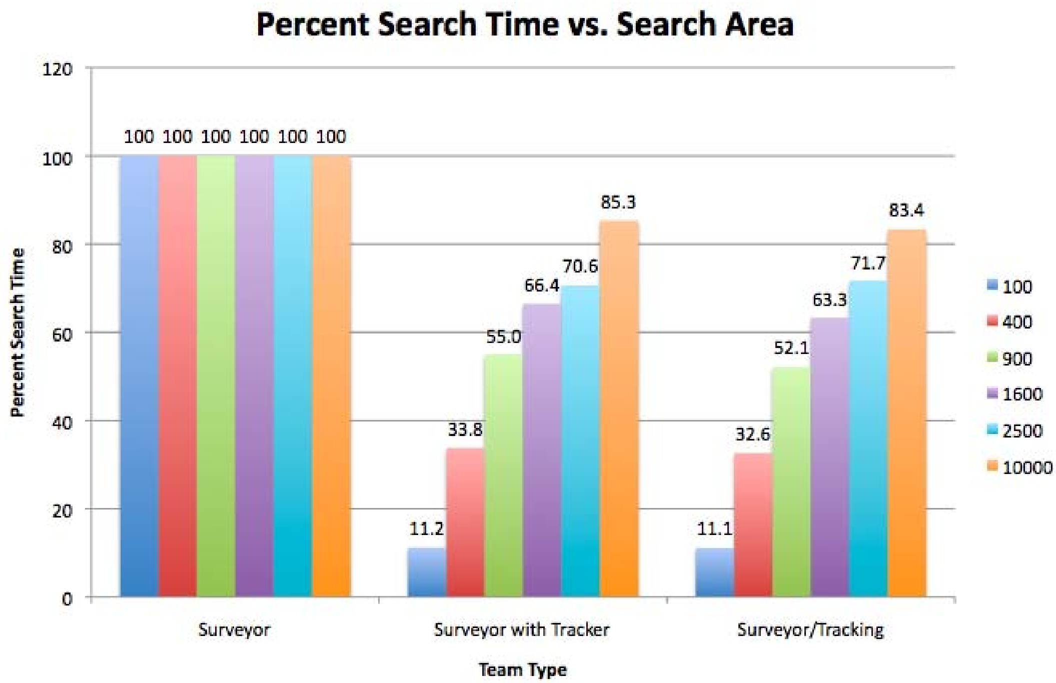


Figure 4.13: Average Percent Search Time vs Search Area Size

for mission accomplishment. For the models above we also found Interdictor Transit Time to be a limiting factor for the cases where we studied team types with a tracking capability. The QRF can only clear the targets it can get to during the course of a mission and this is limited by how fast it can get to each target. The effect of increasing or decreasing Interdictor Transit Time is an area worthy of future study. If it makes a difference in terms of the percentage of targets cleared, then an analysis of alternatives may be necessary to determine the best form of mobility for the QRF of the future.

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CHAPTER 5: Conclusions and Recommendations

We set out to answer the following research questions:

- Is it better for an interdiction team to possess an organic "augmented tracking" capability in the context of time to intercept and number of targets captured?
- What are the significant factors that produce teaming strategies that result in the greatest number of hostile targets captured?

The analysis also shows that while the tracking capability is better, the QRF possessing an organic tracking capability had no effect on either of the MOEs. We also explored three Team Types to determine which factors affect the success of those Team Types in terms of the percentage of targets cleared and the percentage of time the surveyor searches. Those factors are Team Type and Search Area size.

5.1 Search Area

It was not surprising to learn that as the Search Area increased, fewer targets were captured. This was true regardless of the Team Type employed. While not used as a prediction tool, the results of this simulation provide useful insights to a commander who is planning for a mission utilizing teams similar to the ones studied here. Based on the given AOI, the commander may elect to employ a greater number of teams or partition the AOI into smaller sections and employ teams in each partitioned area.

5.2 Team Type

Through the analysis, we were able to show that possessing a tracking capability is superior to no tracking capability. When tracking was present in the Team Type, the number of targets cleared for a given mission is greater than when tracking was absent. Assuming that the Surveyor is national asset and there may only be one available for the AOI and it may be unable to track until released by the QRF or Tracker, the team types employed should include a Tracker UAV. This would allow the Tracker to be launched to the reported target location and get "eyes on" the location to track the target. If the target is not found, the Tracker can then perform a search as the QRF approaches in an attempt to reacquire the target.

5.3 Future Works

As previously mentioned, an area for future research is the effects on the MOEs of multiple teams in a given AOI. Specifically, a heuristic can be developed that can attempt to maximize the number of targets captured by minimizing the time it takes for an interdiction team to arrive at a target location. This algorithm can solve a shortest path problem to the target from each team, identify the closest team, and then through an interface with SASIO an order will be sent to that team to begin the interdiction mission.

We showed that the Interdictor Transit Time was a limiting factor in the percentage of targets captured. An analysis of alternatives can also be conducted to determine the fastest form of mobility for a QRF based on current or future systems. A reduction in the transit time should lead to an increase in the percentage of targets cleared in a mission.

Other areas where the SASIO analysis tool would be useful include the Navy's use of Unmanned Underwater Vehicles (UUV) and the USMC study of cargo UAS for battlefield resupply. The Navy envisions the UUV to have shallow water capability, stealth, and the ability conduct ISR as well as antisubmarine warfare and mine laying operations. The cargo UAS problem will be affected by numerous factors including range, payload, altitude and routes. SASIO provides the ability to perform a thorough analysis of the factor space for these problems and determine which factors will significantly affect the UUV and cargo UAS operations. Once these factors are determined a better CONOPS can developed for their use. While these systems greatly enhance surveillance capabilities, their greatest contribution will be their ability to aid friendly forces in making decisions that will directly lead to an increase in the number of hostile targets captured. This is one of the overall goals of these systems. Surveillance is simply a sub-problem of the surveillance and interdiction mission set.

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APPENDIX A: NPS-USSOCOM Field Experimentation

A.1 General Description

Field experiments were conducted to test the various teaming strategies previously described. The experimentation was conducted as part of the USSOCOM-NPS Field Experimentation Cooperative Capabilities Based Experiment (CBE) 10-3 at Camp Roberts Army Reserve Base.

Assets used included two Raven UAVs to simulate the Surveyor and Tracker UAVs as well as three ground vehicles to simulate the blue team QRF and two red team target vehicles. The Raven UAV is a Group one UAV according to the Joint-UAS definition. It has a wingspan of 4ft 3in and a length of 3ft 7in. It weighs 4lbs 3oz with a range of 6.2 miles or roughly 10 km.

Each vehicle was equipped with a radio and handheld global positioning system (GPS) unit to record position and the time of significant events. The data was collected at the TOC and stored locally with each vehicle for post-experiment playback and analysis.

The controllable variables for these experiments included Team Type, Search Pattern, and the number of objects with the understanding that we would not be able to control the number of objects in any AOI. The uncontrollable variables were the remainder of the factors in Table 3.1. We did not pick any particular search pattern but instead performed a route search of the Camp Roberts road network. This decision was based on the time constraint of the experiment.

Due to asset and time constraints, the experiment was originally planned to study two teaming strategies (Surveyor/Tracking and Surveyor with Tracker) holding all other factors constant. An operational thread, or script, was provided to blue and red teams for the conduct of the experiment. Multiple experiments were conducted during the allotted time period. After all red teams were interdicted or the FOB was attacked, the experiment was reset for the next iteration.

Operational Lessons Learned

The results of these field experiments validated the belief that the search effort is hard. Locating hostile objects within any size AOI is not an easy task. The results showed that even for a small AOI with known routes of travel for red teams, more often than not, the red teams made it to the FOB before being interdicted by the blue QRF. Detection of Red Force vehicles by the Blue

Figure 1: Raven Launch

Force patrolling UAV (Raven) was infrequent, limited by field-of-view, unsteady full-motion video, and scale of the area of interest (AOI). In some cases the first indication of the presence of the red team came from the QRF at the FOB when the red team came within line of sight of the FOB. Once the QRF made contact with the red team, either from Raven cueing or self cueing, the actual interdiction effort was relatively easy. In today's very uncertain environments, it becomes imperative that the search effort be successful. Future work should focus not only on MUT but also on optimizing the search effort to increase the effectiveness of the MUT effort.

One of the most significant and uncontrollable factors in any tactical operation is the weather. These experiments validated the need for the right type of UAV being paired with the appropriate mission. Due to equipment constraints one of the Ravens was used as the Surveyor UAV. In some cases, the Surveyor lost track due to head winds reducing its ground speed to the point where it was no longer able match the red team velocity and thus the red team drove out of the Surveyor field of view and contact was lost. Constraints in real-world settings should be considered in decision support models for employment.

Weather is a valid consideration at the tactical level also. The situation encountered above may alter the decision to launch a Raven as a tracking asset if the weather might make it impossible for it to track. In these situations, the Surveyor would be required to perform a greater share of the tracking mission and thus, we would expect fewer hostile objects to be found. The current SASIO model does not take into account weather effects. Weather and its effects on teaming

and decisionmaking is an area that should be considered for future study. CBE 10-4 scheduled for August 2010 will continue these efforts.

A.2 Operational Thread Script

Surveyor / Tracking

T-0: SURVEYOR launches on a broad area surveillance mission and receives tasking from SASIO/Command to search a given location for a mounted target (RED Team SUV)
- Intel developed and passed to SURVEYOR through TOC
- SURVEYOR: transitions to suspected RED Team location
- QRF: stationary at FOB awaiting tasking from TOC

T-1: SURVEYOR locates RED Team SUV
- SURVEYOR: RED Team location report passed to TOC
- TOC: updates SASIO:Command
- QRF: receives tasking from TOCC to interdict RED Team SUV at reported location.

T-2: SURVEYOR transitions to tracking of RED Team SUV
- SURVEYOR: begins overhead orbit of RED Team SUV. Reports orbit location via SASIO: Command
- TOC: updates SURVEYOR position in SASIO: Command
- QRF: acknowledges receipt of RED Team location to TOC. QRF begins transition to reported RED Team location

T-3: QRF arrives at reported RED Team SUV location
- QRF: reports arrival at RED Team suspected location and reports to TOC
- QRF: identifies RED Team and releases SURVEYOR. Makes report to TOC
- SURVEYOR: receives new tasking from TOC via SASIO: Command
- QRF: begins clearing of RED Team.

T-4: QRF checks for new tasking
- QRF: reports end of clearing operations to TOC
- QRF: request additional tasking from TOC

T-5: If a new report is present, QRF transitions to new RED Team SUV location. If no new report, QRF returns to FOB

T-6: After all RED Team targets are captured or at the end of the experiment, SURVEYOR and QRF will RTB

• Collect Data
o Number of RED targets reported
o Number of RED targets cleared
o Amount of time SURVEYOR searched
o Amount of time SURVEYOR conducted other tasks
• Collect Video of Mission
o SURVEYOR video of identified RED target

Surveyor with Tracker

T-0: SURVEYOR launches on a broad area surveillance mission and receives tasking from SASIO/Command to search a given location for a mounted target (RED Team SUV)
• Intel developed and passed to SURVEYOR through TOC
• SURVEYOR: transitions to suspected RED Team location
• QRF: stationary at FOB awaiting tasking from TOC

T-1: SURVEYOR locates RED Team SUV
• SURVEYOR: RED Team location report passed to TOC
• QRF: receives tasking from TOC via SASIO: Command to interdict RED Team SUV at reported location

T-2: SURVEYOR transitions to tracking of RED Team SUV
• SURVEYOR: begins overhead orbit of RED Team SUV. Reports orbit location
• QRF: acknowledges receipt of RED Team location to TOCC. QRF begins transition to reported RED Team location

T-3: QRF begins transition to reported RED Team SUV location
• QRF: begins transition to reported RED Team location
• SURVEYOR: continues orbit over RED Team. Provides video feed to QRF and ground station
• TOCC: updates SASIO:Command with SURVEYOR location and RED Team activity

T-4: QRF launches TRACKER at predetermined distance
• QRF: launches TRACKER to RED Team location. Reports launch to TOC
• SURVEYOR: continues overhead orbit and providing RED Team location updates
• TRACKER: begins transit to RED Team location

T-5: TRACKER arrives at RED Team location

• SURVEYOR: conducts handoff of RED Team with TRACKER
• TRACKER: assumes tracking responsibilities of RED Team
• TRACKER: releases SURVEYOR for additional tasking
• SURVEYOR: receives new tasking from TOC
• QRF: continues transit to RED Team location

T-6: QRF arrives at reported RED Team SUV location

• QRF: reports arrival at RED Team suspected location and reports to TOC
• QRF: identifies RED Team and releases SURVEYOR. Makes report to TOC
• TRACKER: RTBs to QRF • QRF: begins clearing of RED Team

T-7: QRF checks for new tasking

• QRF: reports end of clearing operations to TOC
• QRF: request additional tasking from TOC

T-8: If a new report is present, QRF transitions to new RED Team SUV location. If no new report, QRF returns to FOB

T-9: After all RED Team targets are captured or at the end of the experiment, SURVEYOR and QRF will RTB

• Collect Data
o Number of RED targets reported
o Number of RED targets cleared
o Amount of time SURVEYOR searched
o Amount of time SURVEYOR conducted other tasks
• Collect Video of Mission
o SURVEYOR video of identified RED target

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APPENDIX B:
Primer on Statistical Analysis Using JMP

Overview

This appendix will provide the reader with the steps necessary to construct a design matrix in JMP [10] and perform screening analysis. This appendix assumes the reader has access to a current version of JMP and is familiar with the basic statistical operations.

Step 1

Open JMP and select DOE from the menu bar, then select Custom Design

Figure 2: Choose DOE

Step 2

From the custom design dialog window under Factors, select Add Factors

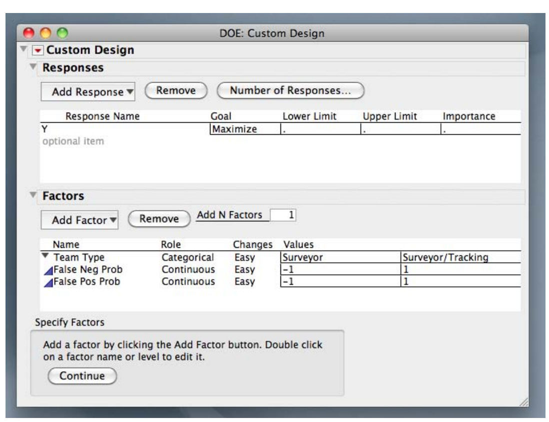

Figure 3: Add Factors

Add all factors and specify their type or role and the associated values. Values can be added as coded variables for analysis or the engineering units can be added at the high and low levels for input into a simulation model such as SASIO. Once all factors and levels are entered, select Continue.

Step 3

Select Interactions, then select 2nd to build a design matrix with main effects and 1st order interactions. Then select Make Design.

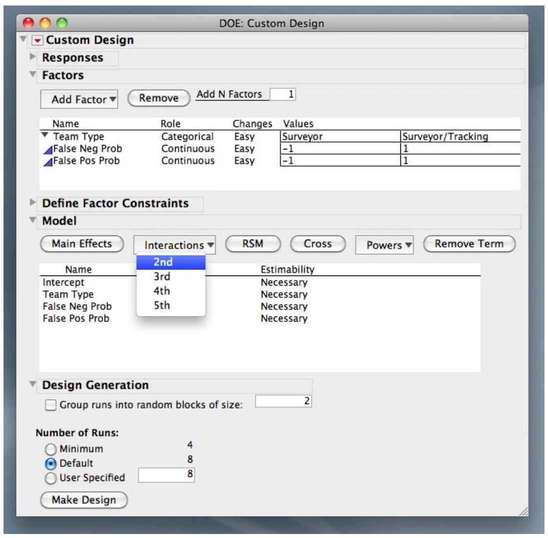

Figure 4: Interactions selection

After interactions are selected the model box should show the interactions

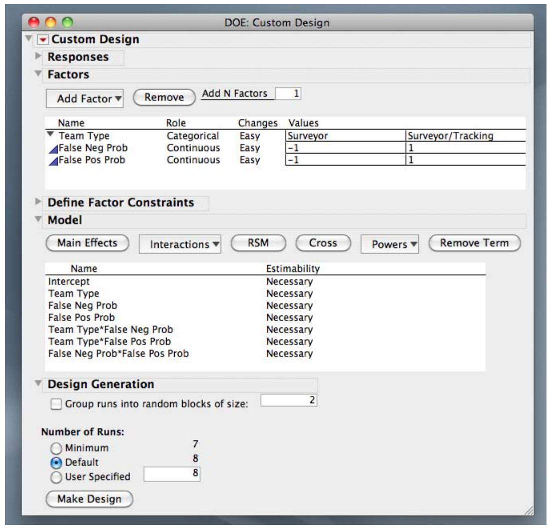

Figure 5: Model with Interactions

Step 4

Before selecting Make Table, select the red triangle next to Custom Design, select Optimality Criterion, select appropriate criterion. For this model we chose to use D-Optimality.

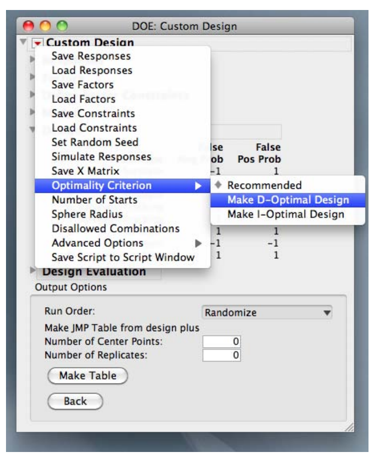

Figure 6: Optimality Criterion selection

Ensure Run Order is set to Randomize. This is found under Output Options. Now select Make Table.

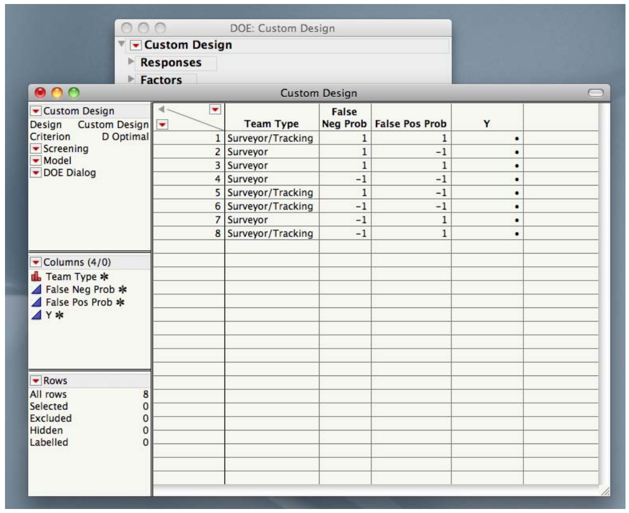

Figure 7: Design Matrix

Step 5

After deleting the Y column, the design matrix is now available to exported to Excel or saved as a txt file for import into a simulation model.

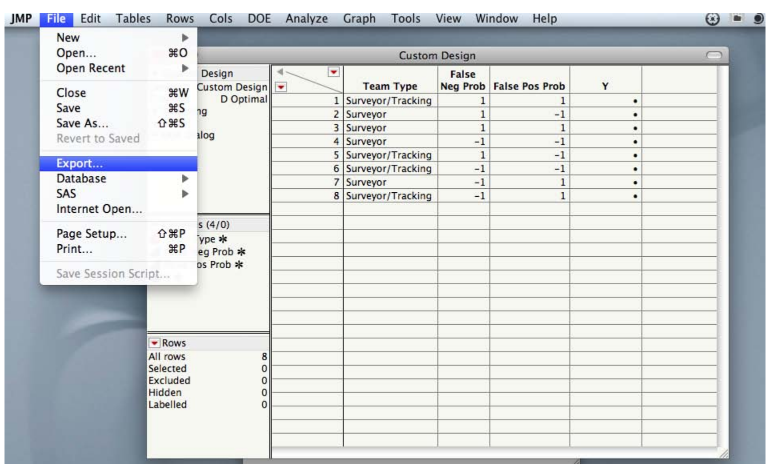

Figure 8: Export to Excel

Select export format.

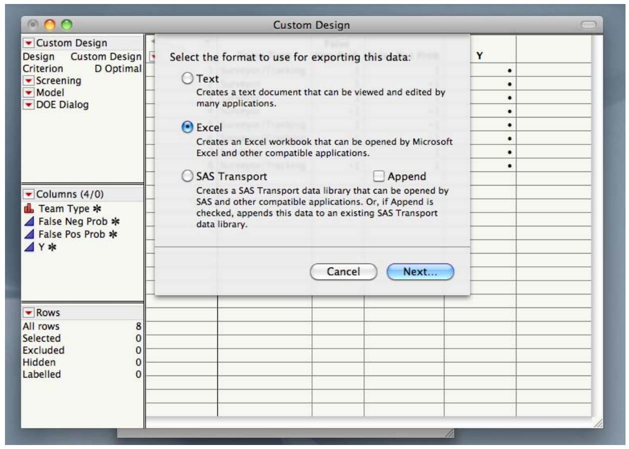

Figure 9: Export Format

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